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|  | **Eyeglasses Prediction Based on Image Processing Techniques.** |
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## Abstract:

In this work, I am presenting an accurate glasses detection technique for classification, distinguishing between human faces with and without spectacles. According to the concept that items with stable and complex structures in a simple backdrop are much easier to identify, I present to detect the eyeglass for searching Region because the eyeglasses have much complex system in the face. This research has looked at machine learning-based architectures and demonstrated their viability on vast datasets of facial pictures. I have utilized the nosepiece area of the glasses for training a new detector with hairlike properties because it has a lot of fixed structures and a simple backdrop. Because of their great accuracy compared to other approaches, the techniques employed for the whole face recognition process are machine learning-based. Face detection is served as a precursor to face recognition, which has used Haar-like characteristics. Face recognition and soft biometrics for person identification rely heavily on the detection of glasses. However, in real-world application situations, automated glasses recognition remains a difficult challenge because facial changes, light circumstances, and self-occlusion all significantly impact its performance.

# Chapter 1

## Eyeglass detection:

One of the fastest-growing and widest-applied areas of image processing is biometrics. In recent years, the growing usage of biometric technologies has boosted its appeal. Unpredictability in the picture generating process, including image quality and photometry, geometry, occlusion, modification, or disguise, makes face glasses identification a very difficult challenge. Two new studies on face recognition (Chihaoui *et al.*, 2016) (Farokhi, Flusser, and Sheikh, 2016) in-depth discussion of these concerns. Today, all commercially available face processing systems work only on a restricted database of images classified by size, age, gender, and race. They can only operate in well-controlled environments.

Allowing computers to adapt to this environment is the ideal course of action. This requires computers to detect eyeglasses, i.e., determining whether or not a face is wearing glasses. Numerous environmental factors, including light changes, face rotation, and expressions, can significantly affect the identification of drinks, making it challenging. In recent decades, approaches for identifying faces, such as neural network-based face detection, have improved fast (Abiodun *et al.*, 2018). Viola and Jones (Viola and Jones, 2004) suggested a method for quick object detection based on a boosted cascade of hairlike properties to improve face identification accuracy.

Following that, it became increasingly vital to research hairlike properties and AdaBoost. Viola invented asymmetric AdaBoost to increase the robustness of categorization. (Lienhart, Kuranov, and Pisarevsky, 2003) For face recognition, we examined discrete AdaBoost, real AdaBoost, and mild AdaBoost. He augmented the hairlike characteristics with a set of 45° rotated features. Although various face recognition algorithms have been given, the performance of a face recognition system may still be impacted by several unfavorable circumstances, one of which is occlusion caused by glasses.

A collage of a person's face

Description automatically generated with medium confidence

***Figure 1.1: Glasses detection from the human face***

Preprocessing is used in the eyes recognition strategy to filter and trim face images. Circular Hough Transform detects the circular shape of the eye and correctly labels the pair of eyes on the picture correctly. The Face DB database created by Park Lab at the University of Illinois in Urbana Champaign in the United States was used to test this eye recognition method. The majority of the faces have their eyes open and are frontal, although a few are tilted upwards or downwards for various reasons. Nearly 86% of the time, the suggested method is accurate in detecting the target substance. Face detection in this work is done without first detecting the face area, as the main goal is to observe an eye pair from the face image. This work uses the known face region to conduct face detection. A simple but effective technique for finding the eye pair is demonstrated on images of faces with low grey intensity. Since various promising face recognition algorithms were available at the time, this study makes the following assumptions: a rough facial region has been detected, the picture only contains one face, and eyes may be seen in the face image. Retraining samples are required for the most efficient in-plane rotating face detection systems. With the help of this research, we're hoping to make glasses detection more resilient to small changes in PIE values. The authors propose a DCNN-based method for determining whether or not a person needs reading glasses based on problems with computer vision. (Simard *et al.*, 2003). They built the DCNN model using public and private datasets of facial images with and without spectacles. These photographs of people's faces were taken during PIE. To evaluate the DCNN model's resilience, we use both the LFW and our datasets. Our results show cutting-edge performance on face photos with apparent PIE

Programmed dietary checking involving body-worn sensors has numerous applications in infection anticipation and sickness the board, principally identified with criticism and training. To get applicable data on food admission, checking of admission-related conduct should be constant without interference or holes.

A collage of a person

Description automatically generated with medium confidence

Figure 1.2: Glasses and without glasses samples

In the course of the last decade, numerous dietary observing gadgets have been created to assess consumption from biting, gulping, and related body movement. Albeit a few observing gadgets showed promising execution, applications stay restricted because of low wearing solace. Sensors attached to the head and neck area (for example, to monitor biting and gulping) are often exposed to the social atmosphere while using dietary monitoring devices. Sensors that can't be stowed away from the point of view of others create safety and defamation problems. Gadgets might be integrated into ordinary items that are comfortable to wear and accepted by the general population in order to make calorie counting realistic on a daily basis. Eyeglasses may prove to be a useful accessory for keeping tabs on one's food. It's better to include wearable frameworks into clothes as clever items of clothing or wearable accessories. Even if they look to meet all the requirements for everyday usage, customary eyeglasses may also allow for substantial estimating locations at the head. Eyeglasses are well accepted by the general public and provide acceptable long-term comfort when worn. In the United States alone, 75% of the population uses remedial focal points, and 64% use eyeglasses. Using eyeglasses as a regular checking device appears to need keeping up with the typical eyeglass structural factor. As a result, smart eyewear looks in a different light than data-gathering glasses-addons for CEOs like Google Glass. Utilizing standard eyeglasses plans anyway obliges sensor and gadgets situating and along these lines is possible lessening signal-to-clamor proportion SNR. For instance, biting can be helpfully estimated from the Temporalis and Masseter muscles compression utilizing Electromyography. Nonetheless, coordinating EMG-based biting checking into eyeglasses requires problematic anode mounting positions along the eyeglasses outline and nonstandard dry terminal sorts.

## Methods

Using tensors, their forms, and their mathematical intricacies, allows developers to focus on the most important aspects of meaningful learning, such as creating layers of neural connections. The backend for Keras should be TensorFlow (or Theano or CNTK). Keras may be used for large-scale machine learning applications without the need for TensorFlow (or Theano or CNTK). The progressive API and the utilitarian API are the two most important types of designs. Keras's most noteworthy use and the easiest part is the back-to-back API, which depends on the randomness of a series of layer actions. It is possible to think of the progressive Model as a linear load of layers. For example, you can easily build a progressive model that includes convolution, max pooling, activation, dropout, and bundle normalization for each layer. Is it possible to develop substantial learning models in Keras by going through essential stages? Once the levels of the Model have been depicted, the disaster work, enhancement, and assessment estimations need to be explained. A 0 or 1, a normally scattered discretionary number, or another useful number is assumed to constitute the underlying weight and inclination considerations at the time the Model was presented. Even yet, the Model's concealed traits aren't exactly what it's looking for. This shows that the concealed weight and inclination gains can't account for the evenhanded/mark-like pointer-like markings (Xs). As a result, it is imperative that the Model's motivation be as strong as possible. Motivation is required for the journey from initial qualities to ideal features, which limits the expense of effort/adversity work. The enhancer suggests that the travel needs to go away (in each accentuation). In addition, an evaluation assessment or estimations of evaluation is required for the journey. It's typical for customers to offer an image power rating based on their appraisal of the image's power, which is a direct measure for recollection of pixels for a particular area. Potential gains on the lower and higher edges should be given consideration. The pixels whose powers are contained inside the stretch are consolidated in the Region forming the estimation. Another approach called neighborhood-related area building has possibly identified a pixel expecting all of its neighbors to have abilities that fit in the stretch, but it is hardly exceptional in comparison to this.

Diagram

Description automatically generated

Figure 1.3: Detection method

A preset range depicts the size of the neighborhood that should be taken into account while rendering each pixel in turn. Mean-regard related Region generating is employed in this study. It is predicated on the knowledge gained from previous visits to the current location. Before any other calculations can be performed, a mean force estimate is calculated for all of the pixels in the area. It is common to depict a deviation from the mean by using a cutoff value provided by the customer. They're identified as being near one other and linked to the Region by the compass's power direction. The Model has to be run on particular data in order to create forecasts once it has been shown and aggregated. Ages and pack sizes are shown here in order to show how many times each cycle of a planned partnership must travel through the list of enlightening occurrences in order for a weight update to occur. As a result of this issue, the software has been running for two or three ages 30 and must complete cycles where the cluster size is, and the educational planning assortment includes events and photos. Again, there is no hard and fast rule for determining the size of a gathering. As long as it isn't the identical size of the instructional preparedness record, it should take up less storage space. After finishing the convolution, it was suggested that the picture stack be pushed back. When looking at the width of the progression, this one has some of the nicest poling. At this moment, it begins to pan across the image in little sections. Pooling reduces the dimensionality of every component map. In convolutional neural systems, normalization is often achieved by adjusting direct units (ReLU). All of the negative features are removed from the limited image using ReLU. This ReLU cycle remembers the Model's non-linearity. Next, a classifier was discovered in the form of a convolutional neural connection in the subsequent layer. Throughout this project, Google is used to arrange images and predict customer expectations. When it comes to Google Colaboratory, the shorthand for it is simply Colab. The Jupyter Notebook is required for Colab's simulated intelligence and deep learning activities. Runtime GPU access is provided by Google Colab for free. The Google collaboratory is useful for PC vision and other GPU-controlled applications. It is necessary to check the presence of the neural connections on the instructional ready files after arranging them on the files. Please note that at this stage, it does not know what the algorithm will do with fresh data; it just knows how effectively the enlightening file was shown. There are certain advantages to limiting data to train and test instructive lists, but this is for simplicity's sake. Your Model may be evaluated on the basis of your preparedness instructional record utilizing the evaluation() work on your Model, and the results can be passed on. As a consequence, scores have been gathered for every data and outcome combination, including the usual difficulty and any guesses, in a manner comparable to accuracy. Keras uses a remarkable and straightforward substantial learning library on top of TensorFlow/Theano to provide crucial level neural connections. TensorFlow tensors may be used in Keras' layers and models, making it a whole new feature for TensorFlow. This library will be used in conjunction with other TensorFlow libraries.

EMG can be used to detect a patient's habit of chewing on their spectacles. Our eyeglasses are 3D-printed versions with woven terminals attached to the edge that can be adjusted to fit various faces. Our goal was to answer the question of whether EMG can be used to detect biting through the use of eyewear. Commitments to the related promises are outlined: We're looking at the best EMG terminal placements for those wearing spectacles. Aside from that, we examine cathodes with gel or dry texture in terms of dissecting combination, with an eye on terminal size. The unique cathode circumstance, size, and type changes were taken into consideration while determining signal execution and SNR. We provide methods for detecting biting from cathodes coupled to spectacles and present results from small research, including eight glasses wearers. Model-savvy eyewear was 3D-printed for the assessments. In addition, we look at signals from food surfaces to discern various food categories.

## Face normalization

Body-worn sensors may be programmed to monitor a person's nutritional intake, which has several applications in the field of illness prevention and illness management. Admission-related behavior must be observed continuously without interruption or gaps in order to obtain valuable information on food intake. Various nutritional monitoring devices have been developed during the last decade to evaluate intake through biting, gulping, and associated body movements. However, despite encouraging results from a few gadgets, applications remain limited due to low wearer comfort. As a result, many dietary monitoring devices require sensors attached to or worn around the head and neck, for example, to monitor biting and gulping). Security problems and the risk of trashing are raised by sensors that are difficult to stow away from the point of view of others. Gadgets might be integrated into ordinary items that are comfortable to wear and accepted by the general community in order to make nutritional monitoring possible on a daily basis. When it comes to checking your nutrition, eyeglasses may be the most wearable extravagance. Because they are used on a daily basis, wearable frameworks should be integrated into clothes or other items as wearable accessories. It appears that normal spectacles are well suited for daily usage while maybe providing access to crucial areas at the head. Wearing eyeglasses for a lengthy period of time is generally acceptable in society and provides appropriate comfort. 75% of the population in the United States uses restorative focal points, and 64% wear eyeglasses. Using eyeglasses as a constant checking device appears to need keeping up with the normal eyeglass construction. Glasses-add-ons for data collection, like Google Glass, stand out in comparison to brilliant spectacles. Wearing glasses that don't have sensors or other devices attached is an acceptable technique to reduce the sign-to-commotion ratio. Electromyography can be used to accurately quantify a person's habit of biting, for example. Anode mounting places along the eyeglass contour and nonstandard dry cathode types are required for EMG-based bite checks to be implemented in spectacles. EMG can be used to detect a person's habit of biting. Our spectacles are 3D-printed prototypes with woven anodes that can be adjusted to fit the wearer's face. Using EMG, we wanted to see if eyeglasses could be used to detect biting. Commitments to the accompanying promises are also made: For eyeglasses combination, we dissect EMG cathode layouts that are acceptable. Additionally, we take a look at anodes with gel and dry textures. This stage of facial recognition computation is commonly overlooked. In other cases, the arrangement of the eyes is made physically, in which the locations of the eyes are identified. According to the premise that the face recognition computation will play out an arrangement, this development is ignored in various situations. Prior to the acknowledgment stage, many acknowledgment computations rely on precise positioning of the facial Region in a normal posture.

A collage of a person's face

Description automatically generated with medium confidence

Figure 1.4: Face Normalization

At the very least, for calculations that are sensitive to misalignments, this arrangement interaction can lead to an increase in recognition precision on real images. Proposes a method for creating an arrangement machine for an article class by manipulating images that have been incorrectly adjusted. Unaided element learning is used in conjunction with a solo joint arrangement to alter images. According to the arrangement of the images, a few tests are carried out. Manual arranging was shown to have a slightly higher order rate than a computerized arrangement strategy. After that, they concluded that the program's layout needed to be updated. In light of the advancements in computer-aided design, this claim, which was significant at the time, should be re-examined. According to, an eye location-dependent face standardization calculation has been presented. The understudies' faces are located in the facial image thanks to the computation. The orientation, scale, and dark size of the facial picture are all standardized from this point onward in the computation. The position of the mouth affects the location of the face. Glasses and other visual obstructions can alter the standardization step's outcome because of this calculation's necessity to locate the students. There is a new face standardization formula. To ensure that all faces have eyes positioned in a comparable place, the countenances are rotated and shifted in the photographs. A photograph is resized when the standardizing process is complete. Face layout and standardization calculations are proposed in this study. A relapse line is drawn based on four markers on the eyes to pinpoint the location of misalignment. A facial tourist spot indication employed in this article relies on the interaction between numerous facial components (eyes, nose, and mouth) in terms of appearance and construction dispersion in order to detect tourist destinations. However, Face affirmation is a major step in the process of limiting the face in the image, which is a critical first step. Since recently, a lot of effort has been placed into revealing one's face. Data-based processes, including invariant facial philosophy, format matching approaches, and appearances-based tactics, have all been used to make systems that can recognize faces in a single photo. Reference has a mind-boggling amount of information on facial acknowledgment. Concealing information, such as seeing the skin map whose tone is similar to the skin's hue, might restrict the general glance through Region. Clear-reach images are used to identify the majority of face ID techniques. To date, the Viola-Jones algorithm20 (first described in 2001) appears to be the most effective visual picture computing method ever devised. Infrared and long-wave infrared photography has been used to reveal the face in a few articles. In contrast to more obvious images, warm imaging has a distinct benefit when it comes to capturing a variety of facial appearances in different lighting situations. Glasses appear to be completely opaque to IR light. They suggested a face-area system susceptible to near IR phenomena and multi-band feature extraction in Reference. There is no correlation between the arrive at and the warm releases since it lies within the reflected portion of the infrared reach. Pictures taken with a NIR camera aren't precisely the same as those taken with a warm camera. An eye and eyebrow check plot is used later in skin division to determine whether or not a person has a full face. To distinguish faces in warm images, the authors of Reference developed a thresholding and projection approach. Based on Reference's concept, this study presents a new approach. Facial ID's goal is to identify a person's face district from a photograph. The following diagram illustrates how to estimate a person's facial disclosure. Using an area-producing computation, smooth the image and segment the person in it so that the individual's state can be obtained; next, do morphological tasks (closed and open) to eliminate the disturbance division. Make use of a massive (5x5) morphological element and repeat the message twice if necessary; Smooth the projection profiles (curves) by calculating two projections in a uniform and vertical manner (first and second auxiliaries). Do a variety of smoothing assignments before moving on to the next step. Use the base and the most conspicuous auxiliary (identified with the spaces of the most abrupt alterations) to conclude the face location for a vertical projection and a level projection.

A picture containing text, donut, different

Description automatically generated

Figure 1.5: Normalization

Prior to searching for the base and usually ridiculous, apply a smoothing movement to the vertical projection of the important subordinate. To make the even projection appear absurd, they're integrating the local least with the exaggerated traits. Snarky traits can be found in these small green circles: For example, draw a red rectangle on the initial or binarized photo and save the recognized face picture a few minutes later; some goals are considered to make the area more accurate and enthusiastic, such as the length of the head should connect with half of the length of the shoulder; The twist in the projection is also smoothed by using a higher solicitation smoothing algorithm. This face-revealing estimate uses a calculation that creates a locality for the division. The use of estimates to divide an image into distinct regions has been proven to be effective. Creating a new region in a computer begins with a seed area that is believed to be inside the entity that has to be separated. In order to determine whether or not they should be considered part of the object/region, connected pixels are examined. All new pixels are contributed in a collaborative effort until all new pixels have been added. The actions utilized to remember a pixel for the space or not, the caring accessibility used to pick neighbors, and the approach used to visit adjacent pixels all conflict with the region-creating estimations. Setting credits are extremely important for eye constrained when the form or power characteristics of the eyes cannot be properly measured due to barriers (such as wearing glasses or sunglasses). In general, other facial features such as the look and developmental assignment of the eyes in the face setting have consistent interaction with each other. Consequently, a record of facial accomplishments gained through a synchronized end result SVM has been used to identify the places on the face and, in this way, the eyes of the most important anxieties. The classifier's commitment is a single face in a fixed-size still picture. As a result of using a classifier, several facial successes are examined. An outline with eight components is being regarded as a requirement. The LFW database was used to test the classifier's accuracy. Photos are checked for a mean normalized discrepancy between their assessed and ground truth locations of roughly 97%. Using this technique, you may detect the position of the eyes that are occluded, such as while wearing glasses or sunglasses. Cathode size should be taken into account while planning dissection. Various anode layouts, sizes, and kinds were tested for SNR and signal execution. Biting may be detected with the use of EMG anodes attached to eight pairs of spectacles. A 3D-printed eyeglasses model was utilized in the experiments. The information included in the EMG signals generated by food surfaces is also analyzed in order to isolate various food types.

## Research background

Machine learning has recently been applied to enhance the detection of glasses. Before this research in the literature review, I conceded the several theories which are: Proposes an eyewear detection method for thermal face recognition, with excellent detection accuracy In this research (Wu *et al.*, 2002), Only 23 glasses with images from the ASUIR database are used to measure performance. Fernandez et al. (Fernandez Casado and Usamentiaga, 2015) Using hairlike properties and the AdaBoost algorithm, it was suggested. To summarize, the most available approaches for detecting glasses are based on handmade properties (Du *et al.*, 2017). Using hairlike properties and the AdaBoost algorithm, it was suggested. To summarize, the bulk of available approaches for detecting glasses are based on handmade properties.

Deep learning has recently gained a lot of attention. The fundamental advantage of deep understanding is that its algorithms can automatically extract high-level, abstract knowledge as data representations during the complicated learning process. This paper (Karunakaran, Joseph, and Pandiaraj, 2021) offers an approach for identifying glasses using deep convolutional neural networks (DCNNs) based on prior research and is motivated by this work. A deep convolutional neural network (DCNN) dubbed Glasses Net, or GNet is formed and taught as a face identification network by training it on many different people's faces. After that, a fine-tuned version of the GNet is constructed to discriminate between images of people wearing glasses and those without spectacles. Just 23 glasses with pictures from the ASUIR information base are utilized to gauge execution. Utilizing hairlike properties and the AdaBoost calculation, it was recommended. To sum up, the most accessible methodologies for distinguishing glasses depend on handcrafted properties. Utilizing hairlike properties and the AdaBoost calculation, it was recommended. To sum up, the main part of accessible methodologies for identifying glasses depends on high-quality properties.

Profound learning has as of late acquired a great deal of consideration. The essential benefit of the profound agreement is that its calculations can naturally separate undeniable level, conceptual information as information portrayals during the convoluted learning process. This paper (Karunakaran, Joseph, and Pandiaraj, 2021) offers a methodology for distinguishing glasses utilizing profound convolutional neural organizations (DCNNs) in light of earlier examination and is spurred by this work. A profound convolutional neural organization (DCNN) named Glasses Net, or GNet, is shaped and instructed as a face distinguishing proof organization via preparing it on various individuals' countenances. From that point forward, an adjusted variant of the GNet is built to separate between pictures of individuals wearing glasses and those without scenes.

## Aim

The basic aim of this research is to build an AI-based model to target the eyeglasses from the face. Face recognition is used in several aspects of life; however, in this work, the system has classified the face as having eyeglasses from the face without eyeglasses.

## Objective:

* Develop a system using NLP techniques to classify human face eyeglasses.
* Design an ML classifier for the massive dataset based on eyeglasses and without glasses.
* To build a system that provides more significant results and accuracy.
* To build an automatic system which has been used for the detection of the human who is wearing eyeglasses in the public crowd.
* To generate a message when a man has eyeglasses while any checking where no requirement of the face glasses.

## Research Question:

How to differentiate the human faces which have eye glasses and those that have not? Is there any need for a digital system to identify and recognize the eye glasses.?

# Chapter 2

## Related work:

This study (Khairosfaizal and Nor'aini, 2009) uses the Circular Hough transform to locate eyeballs. Since the facial Region has already been recognized, the search for an eye pair is based on the circular form of the eye in a two-dimensional image. Detecting objects, such as faces and glasses, is a critical and significant task for picture retrieval and classification (Du *et al.*, 2017)(Le, Dang, and Liu, 2013) (Zhu, Suk and Shen, 2014). Face recognition is challenging yet complex work since the human face changes depending on internal elements such as facial features, hairstyle, eyebrow, stubble, etc. Meanwhile, outside factors such as size, lighting conditions, in-plane rotation, posture, backdrop, and the like impact face identification. Automatic face recognition is an influential and effective study topic because of its great potential in real-world applications such as identity management, access control, attendance tracking, border control, and surveillance (Chihaoui *et al.*, 2016). As proper face identification improved in speed and precision, more researchers turned to multi-view face detection. Simultaneous AdaBoost learning was solved using Li's Float Boost (Li *et al.*, 2002). Jones (Vikram and Padmavathi, 2017) a fourth rectangular filter to detect faces in several perspectives Li tackled convolution neural network facial detection (Li *et al.*, 2015). Face recognition has several applications, one of which is security. Human security is a significant concern since no one wants to endanger their lives or valuables. An intelligent device is present for security. The street security cameras do not offer information on people who break the law. Many scholars (Zhao *et al.*, 2021) have suggested various approaches for identifying glasses in face pictures. Because glasses detection is a two-class problem, these methods typically extract hand-crafted features from the input face image, such as wavelet features and local binary patterns (LBP), and apply binary classifiers, such as nearest neighbor classifiers, support vector machines (SVM), to determine whether the face has glasses or not.

The performance degrades when used to in-the-wild facial images to obtain highly accurate face photos collected under controlled settings. Wang (Jing, Mariani and Wang, 2000) developed RNDA to perform Multiview face and eye detection.

Appearance eye identification techniques are used to find the eyes by taking advantage of variations in look and form between the eyes and the rest of the face. The AdaBoost algorithm is now used by the majority of detectors (Du *et al.*, 2017). As one type of boosting algorithm, AdaBoost can adaptively modify the weights of training samples and choose the best weak classifiers, then merges them to form a robust classifier. The distinct weak classifiers vote separately. Real AdaBoost has a continuous confidence level in this method; thus, it can show the categorization boundary more precisely than discrete AdaBoost (Wu, Ai and Liu, 2004). As a result, they selected genuine AdaBoost as our face and eye identification algorithm in this study. In particular, to more effectively prevent overlearning, referring to the smoothing factor is not set at a predefined point and has fluctuated depending on the ratio of positive samples' weight and negative samples' weight. Because of its direct relationship with face analysis systems, glasses detection is a critical challenge in CV research. However, there is a scarcity of research that focuses on this specific issue.

The problem was widely handled in the past by localization of the eyes and designating surrounding areas, where glasses are expected. Their existence is tested using grey level discontinuities of the frame relative to the face (Basbrain *et al.*, 2017). In (Wu *et al.*, 2004), eyeglasses were detected using a mix of edge information and geometric characteristics. In another study, the job was completed utilizing edge information inside a narrow region specified between the eyes, known as the nosepiece. To identify and remove glasses, Bayes methods were also employed (Wu *et al.*, 2004). Image descriptors were used to aid in the identification of mirrors in the subsequent period.

Local Binary Pattern was utilized in (Fernández *et al.*, 2015), wavelets in (Wu, Ai, and Liu, 2004), HOG in (Mohammad, Rattani and Derahkshani, 2017), and hairlike features in (Hapsari, Mutiara and Tarigan, 2019). Following their success in defining visual landmarks, three-dimensional characteristics were utilized to identify glasses. Recently, the use of DL-based methods has grown quickly throughout several domains of CV. This is since DL-based approaches do not suffer from weariness or mood swings, allowing them to analyze massive quantities of data at unimaginable speeds while surpassing humans in terms of accuracy. The Caffe framework (Drozdowski *et al.*, 2018) was used to recognize glasses from an iris picture collection.

Furthermore, this dataset does not represent entire faces but just frontal clipped ocular areas. Later a two-stage CNN was proposed, but the complete trials were carried out using 23k pictures for testing and just 1k images for validation. In (Mohammad, Rattani, and Derakhshani, 2019) suggested a new CNN architecture based on adversarial learning.

The glasses collect data from a camera attached to them and then display the results. This section reviews the needed hardware, then discusses the software strategies utilized. In (Wang and Chen, 2006), wavelet characteristics are presented, and AdaBoost is used to identify the glasses. This approach performs admirably on the public database FERET. However, in each of these systems, all of the testing data are frontal face images. In (Wu *et al.*, 2002), The authors propose a technique for recognizing glasses frames using the three-dimensional Hough transform that takes advantage of the three-dimensional properties gathered by a trinocular stereo vision system. However, this strategy necessitates the use of more cameras and processing time compared to earlier 2D systems.

Machine learning has recently been applied to enhance the detection of glasses. Proposes an eyewear detection method for thermal face recognition, with excellent detection accuracy In this research (Wu *et al.*, 2002), Only 23 glasses with images from the ASUIR database are used to measure performance. Fernandez et al. (Fernandez Casado and Usamentiaga, 2015) Using hairlike properties and the AdaBoost algorithm, it was suggested. To summarize, the most available approaches for detecting glasses are based on handmade properties (Du *et al.*, 2017). Using hairlike properties and the AdaBoost algorithm, it was suggested. To summarize, the bulk of available approaches for detecting glasses are based on handmade properties.

Deep learning has recently gained a lot of attention. The fundamental advantage of deep understanding is that its algorithms can automatically extract high-level, abstract knowledge as data representations during the complicated learning process. This paper (Karunakaran, Joseph, and Pandiaraj, 2021) offers an approach for identifying glasses using deep convolutional neural networks (DCNNs) based on prior research and is motivated by this work. A deep convolutional neural network (DCNN) dubbed Glasses Net, or GNet is formed and taught as a face identification network by training it on many different people's faces. After that, a fine-tuned version of the GNet is constructed to discriminate between images of people wearing glasses and those without spectacles.

Interest in facial image analysis, encompassing tasks like face recognition and inquiry, has grown rapidly during the past few years. Fewer publications have been written about the finding of glasses, although there are still a few investigations in this area (a short portrayal of the aftereffects of principle studies on glasses identification should be visible. (Mohammad, Rattani and Derahkshani, 2017) six probability metrics for determining the existence of glasses in distinct districts are described. As a result, a combination of them is able to consistently show each individual metric. The nosepiece of the spectacles was shown to be the most significant indicator of glasses recognition in tests. The location and extraction of glasses are discussed in another paper. Edge data is used to pinpoint a specific location between the eyes. The technique outlined in] applies to discovery as well. The nosepiece, as referred to in, is perhaps the most well-known component of the complete frame. With a flexible shape, a condensed edge, and mathematical highlights, extraction is achieved. Using Bayes rules, glasses detection and removal for face recognition are suggested in (Miyakoshi and Kato, 2011). This method was tested in a face photo data set and found to be feasible and preferable to the one. Extraction is recognized using Bayes decisions that combine the elements around each pixel and the previous information about glasses that were learned and stored in a data collection. To remove the glasses, an adjustable center channel is focused in the areas referred to as "glasses." this proposes a method to locate glasses outlines with 3D Hough change using 3D highlights from a trinocular vision framework. In 3D space, it relies on the position of the glasses' edges relative to each other. In comparison to previous 2D picture-based systems, this one needs a higher number of cameras and computing time. To describe facial credits introduces an organizational framework. This study enhances the Eigenface method by adopting a 'facial trait explicit subspace to address each characteristic of the Eigenface. Additionally, wavelet-based support techniques can be used for glasses recognition. Initially, this method was derived from studies on facial recognition. Genuine AdaBoost is a first-generation assistance computation used by the glasses finders. For glasses discovery, creators advocate looking at the nosepiece of the glasses outline. proposes a formula for identifying, limiting, and evacuating spectacles. The location of the eyes and, thus, the location of the eyeglasses may be discovered using a detached eye area finder. In the design of the eyeglasses, the eye area is twice as large as is well acknowledged. A Markov chain Monte Carlo method is used to complete the limitation of eyewear (Valstar *et al.*, 2010). A front-up facial photo may be used to detect glasses using a Delauney triangulation-based approach. Despite this, they decompose at an incredibly low rate. Furthermore, if the glasses don't cover the eyes, they don't get great results. It is used to give an integrated picture for eyeglass evacuation that plays out a powerful facial recognition by intertwining visual and warm information together. Two ovals can be used to address the location of the eyeglasses in warm face photos. A method for removing the wearer's spectacles from a photograph of their frontal face has been presented (Zhang and Amft, 2017). Using color and form data, the glasses area is naturally segregated. They remove spectacles, but they don't look for them. To begin with, the glasses district is eliminated using shade and form data, and then a natural-looking face image sans spectacles is created by PCA recreating. Using glasses evacuation techniques, they were able to enhance acknowledgment execution after conducting a few analyses. A total of nine Viola and Jones finders were created. Glasses are sorted according to by kind. Shades, eyeglasses, and a lack of them are all recognized by them. Individual differentiating evidence can be provided by using delicate biometrics (such as spectacles). They use a formula discovered in to locate the edges of a dark-level image. Research in this area has focused on identifying acceptable estimates to evaluate admissions-related behavior since the field's infancy. Head and neck were instantly identified as prime targets for biting and swallowing. It's possible to gather important information about a person's intake by observing how they bite and swallow their meal (Zhang and Amft, 2018). Biting microstructure, for example, the timing and correlation of individual bites and swallows to eat a food piece have been shown to have substantial perceptional qualities, such as food preference. An in-ear acoustic sensor was used to investigate the sound of food being squashed during biting . There was a need for compensating methods such as increasing the ear obstruction or calculating distinct noises to decide the admission timing and meal kind. When it came to handling screen sound and recording video with an in-ear device, (Wu *et al.*, 2004) went further. The wearer may be shown a video that relates to the perceived admission occurrences. To determine biting movement, (Farooq and Sazonov, 2017) used a bone-leading receiver and a strain sensor attached behind the ear. Using a piezoelectric sensor attached to the neck, we were able to measure vibrations during biting and gulping and group strong and fluid food kinds. Similar methods have been developed recently that use receivers attached to the neck area to organize meal kinds. Biting can be quantified, according to prior studies. In any event, all of the methods outlined necessitate the usage of special devices attached to the head and neck, which raises safety, mockery, and wearer consistency problems. Alternatively, eyeglasses may be a good fit. As a further point of clarification, EMG was never truly contemplated for preprogrammed diet monitoring up to this point - definitely due to its perceptibility in example estimate frameworks. Glasses with add-ons were also examined for application testing. Google Glass' inertial and light sensors were used by (Zhang and Amft, 2017) to identify different stages of the eating process. In contrast to the use of dazzling spectacles as observation tools, Google Glass was designed to facilitate communication and display data. The initial steps toward using regular eyeglasses to monitor eye growth and activity. They used inertial sensors attached to the lenses of conventional eyeglasses to monitor daily activities. It is possible to use smart eyewear with a standard approach to perform observation in the previous two studies. However, the benefits of using bright spectacles for dietary observation have yet to be proven. EMG anodes mounted to the frames of eyeglasses might be used to monitor facial muscle withdrawal during biting. EMG measurements of the Masseter and Temporalis muscles were used in standard laboratory studies of biting. Compression capabilities and the influence of diet, age, and dental state were often assessed during examinations . Throughout the whole piece, the Masseter and Temporalis muscles were used to evaluate jaw movement. Biting at a pair of brightly coloured eyeglasses may be done with either muscle. It estimate at eyewear is likely to display poorer SNR and antiques compared to lab accounts due to various activities, such as chatting, hacking, and so forth. Commotion consequences are examined in this study. The most important ergonomics plan. When contemplating eyeglasses, the same considerations for exceptional eyeglasses are applicable to bright eyeglasses. The core form and design of spectacles must be maintained, with just a few options available to match the components of a complete electronic framework. In contrast to Google Glass, we do not use optics or communication interfaces in our products. At bright eyeglasses, sensors can only be placed at the outline of the spectacles. There are a few places where the eyewear outline touches the skin that can be used for EMG attachment. When we think of eyeglasses, we think of the typical pair and the standard fit, which is based on the size of the head. Because of this, only nose cushions, sanctuary ear curves, and sanctuary shut provide enough skin contact. Consequently, The EMG signal is likely to be hampered by a lack of skin and hair contact in the sanctuaries at the casing front. The front of the casing is confined to the nasal cushions that are in direct touch with the user's skin. As a result, the EMG indication may be affected by the hair while using an eyeglass extension.

Programmable face recognition is a fascinating research topic because of its wide range of real-world applications. In spite of the fact that facial recognition isn't a trivial undertaking, it may be hindered by things like wearing glasses, which can reduce the effectiveness of the system. Certain glasses can recognize an individual or, in other situations, act as delicate biometrics for individually identifiable proof (framework glasses, U2 glasses(Zhang and Amft, 2017). However, there is a distinct difference in look between men's and women's spectacles, which might help in determining a person's sexual preference.

# Chapter 3

## Methodology

This section explores the information about glasses detection on the face or not we are using images to train our model in which we have two types of images with glasses and without glasses, the process involves :

* Image acquisition
* Preprocessing
* Feature engineering
* Model training
* Testing
* Classification

For the classification of having eye glasses on face or not , two methods will be used: literature review and experiment. Literature review will help to collect information about previous approaches which will further assist in the experimentation purpose.

### Data (Image) Acquisition:

In this phase, the image dataset has to be input for further evaluation. The presence of labeled data sources, like ImageNet, has enabled the Model to infer and learn extensive visual features, resulting in a significant improvement in various optical recognition issues. Furthermore, for the first time, these learned characteristics and representations were harnessed and transferred to a new problem via network reconfiguration. the amount of sample data necessary to train the Model.

### Pre-processing:

Haar-like features have frequently been employed in proper face identification for two reasons: this phase is significantly more important for the number of raw pixels and accurately depict good faces, and it is quick and straightforward to computing method. Haar-like characteristics have directly represented the local relationship between picture areas. The hairlike features may be computed by subtracting the pixel sum of the black rectangular Region from the pixel sum of the white Region. The pixel sum of each rectangular region feature has been derived using integral pictures.

### Region of Interest (ROI)

The Region of interest has a significant impact on every type of research; in this work, I have classified the face glasses; therefore, the first step is to find the target or Region required to solve this problem. After images acquisition and preprocessing, the relevant Region has found various algorithms used in several studies to find the required area, such as Cascaded filters, CNNs, Haar‐like features, and AdaBoost.

A collage of a person

Description automatically generated with low confidence

Figure 1.6 Region of Interest

### Feature Engineering

Feature planning is the endeavor of additional creating farsighted showing execution on a dataset by changing its component space. Existing ways of managing to robotize this communication rely upon either changed part space examination through evaluation coordinated request or unequivocal improvement of datasets with all changed components followed by feature assurance. Such techniques achieve high computational costs in runtime and furthermore memory. We present a unique technique called Learning Feature Planning.

### Model training and Testing:

In this phase, I have trained the Model by the inputted data for the training purpose; first of all, the dataset has to be split for the training and testing, the ratio of the train data and test data maybe 90% and 10%. However, it is not compulsory; it may be changed to improve the Model's accuracy because the core objective of this research is to build a model that provides more accurate and significant results compared to the other state-of-the-art schemes.

Graphical user interface, text, application

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In this work, I utilize the deep neural network-based algorithms such as

* Sequential model-based on CNN
* Restnet50 based on CNN

After the model preparation, most certainly, the following stage is to play out the assessment and approval of the Model. For this reason, the framework needs to test the information subsequent to parting the Model. In this review, I applied restnet50 based on CNN-based techniques to answer an issue. We select the different evened out regulator for quite a long time steps, going to the responsibility at each development and managing the response through the regulator to make the result.

### Workflow: Here is the entire work flow to train machine learning model.

Import Libraries



Import Data



Data Pre-processing



Feature Selection

Train Test Split

Train data

Test data

Model

Prediction

Result

## 4.2 Experiment phases:

In this work, the primary focus of the Model is to detect the spectacles. The first thing is to see the human face and ignore the other irrelevant objects and items from the inputted image. The second important task is to find the eye location from the face, and after detecting the target region, the Model has to see the glasses on the face. The initially proposed to contrive uses to perceive visual District of interest using facial numerical information, followed by glass revelation. Based ROI area using numerical information. In this arrangement, we track down the best width, which is the restriction as perceived. The base width is surveyed in the same plan. Further, we segment the base width by the best width to evaluate the extent. Therefore, to perform this experiment, the system has to work based on the following steps.

* Normalize face
* Eye location
* Find Region of interest (ROI)
* Filtration
* Model training
* Detector

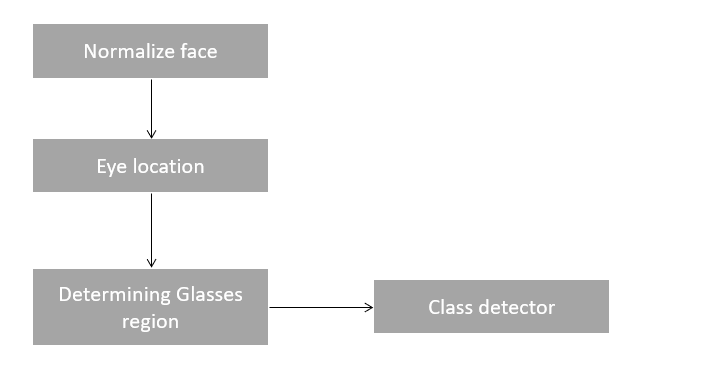


Figure 1.7 : Purposed Framework about the research

The target of the article acknowledgment is to choose if a window has a spot with the level-headed or not, which is a twofold portrayal issue. For the classifier setting up, the assurance of the positive and negative models is huge. The assorted course of action results in various dispersals of the models. In number and void centers mean positive and negative models, exclusively. On one side, differentiating besides, it is seen that positive instances are more thickly scattered than those of, which adds to the result that the display of classifier is pervasive. The clarification lies in when the development of the perceived thing is fixed and staggering, the similarity between the thing and

the establishment is low. Preceding glasses ID, to hinder the irritation of the eyes similarly as to improve on the establishment, we need to conclude the establishment region through the eye position. Thus, we will detail the specific eye region computation first and thereafter unveil how to choose the up-and-comer area of the glasses considering the eye position. The eye is adequately affected by position, upset and light conditions, and in this way, it is badly designed to get a definite eye region. As of now, a couple of experts use picture taking care of procedures to track down eyes, for instance, Hough change and essential projection methodology, anyway these techniques are adequately irritated with the disturbance. To make due to these drawbacks, embraced haar-like components and AdaBoost to perceive eye contender centers, and

then joined the contenders or to choose the last spot of eyes. In any case, the capability is low, and the results are not really consistent. Remarkable according to the above methods, we present a fast and strong eye region estimation considering haar-like features, likewise AdaBoost. First thing, two eyes can be found independently by using the eye locater. Besides, considering the way that the plan of two-eyes is more confusing than one single eye, two eyes are merged together as the revelation concentration to also additionally foster the acknowledgment accuracy. Hence, we can use haar-like features and make a different course to obtain three classifiers: left eye, right eye and two-eyes locaters. Ensuing to concluding the spot of the eyes, the accompanying work is to measure glasses locale. To shed the disturbance of the eyes, we include the spot of left and right eyes as left, what're more right lines of the goal region. Meanwhile, in the nosepiece region, the glasses are basically flush with the eyes; what's all the more consequently, the top and baselines of the revelation are not totally firmly established, as shown by the bearing of eyes. Hence, it discards the agitating impact of the eyes and reduces the up-and-comer area of the glasses. Therefore, the glasses can be recognized viably inside this area rather than the entire face region, for the clarification that if the establishment is fundamental, the goal is easily perceived.

### 4.2.1 Resources Setup

For this experiment, python has been used as the programming language which is an open-source and has a lot of libraries which are easy to implement.Google colab will be used to enhance the training time of images while meeting the study’s memory and CPU needs. Intel core i7 CPU with a RAM of 8 GB running windows 11 operating system is used.

Similarly, various python libraries will be used such as Sci-kit Learn, Numpy, Pandas, OpenCV, Matplotlib, tensorflow,keras and so on.

## Dataset:

A python mechanical get-together is involved for face glasses pictures of the public and their relating pictures from tremendous Internet assets; the relationship of the dataset is accessible in the references. Then, at that point, we truly abstain from the inconceivable pictures occurring by virtue of wrong correspondence. The most generally perceived strategy for separating pictures takes a ton of work.

A collage of a person

Description automatically generated with medium confidence

Figure 1.8 : dataset samples

Fundamentally, we crop the particular face regions with the assistance of the CNN model. The dataset joins the two sorts of pictures having glasses and without glasses. Supposedly, this is before long the current reality dataset for this examination. The figure shows picture tests. To widen the volume and combination of the face certification dataset, we, in the interim, have taken elective means, which is to put on the cover on the current public colossal augmentation face datasets. To moreover encourage information control ability, we have developed a having eyeglasses programming subject to the library to perform along these lines. This thing is then used to confront pictures in the remarkable face attestation datasets, now including datasets. Consequently, we moreover encouraged a reenacted for eye glasses face pictures.

# Chapter 4

## Implementation.

First of all work on the relevant libraries which are numpy, os, pandas ets, A NumPy exhibit—additionally called an "ndarray," short for N-dimensional cluster—depicts memory utilizing the accompanying ascribes: information pointer: the memory address of the principal byte put away in the exhibit; information type depiction: the sort of components contained in the cluster, for example, drifting point numbers or numbers; shape: the cluster's shape, for example, (10, 10) for a 10 × 10 exhibit, or (5, 5, 5) for a square of information portraying a lattice matrix of x-, y-, and z-facilitates; steps: the quantity of bytes skirted in memory to continue to the following component along a given aspect (for a (10, 10) cluster of bytes, for instance, the steps may be (10, 1), or continue one byte to get to the following segment and 10 bytes to find the following column); and banners: characterize factors, for example, regardless of whether we're permitted to adjust the cluster or whether memory design is C-or Fortran-adjoining in C, memory is spread out in "line major" request—that is, lines are put away in a steady progression in memory—though in Fortran, segments are put away progressively. NumPy's strided memory model merits specific consideration, as it gives an amazing method of reviewing similar memory in various ways without duplicating information.

Text

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For instance, consider the accompanying number exhibit: In any prearranging language, unwise utilization of for circles can prompt horrible showing, especially when a basic calculation is applied to every component of an enormous informational collection. Gathering these elementwise activities—an interaction known as vectorization—allows NumPy to perform such calculations significantly more quickly. In this Model, information [ 5: ] takes a cut of the exhibit beginning at file five and proceeding to the furthest limit of the cluster. Then, at that point, y[: 10] takes a cut that beginnings at file 0 and contains ten components separated from the last. Along these lines, y[1:] - y[:- 1] deducts, from every component in the cluster, the component straightforwardly going before it. Playing out the equivalent differencing on the x exhibit and partitioning the two coming about clusters yields the forward separated contrast.

In case we accept that the vectors are length n + 2, then, at that point, computing the focal isolated distinction is just an issue of adjusting the cuts: NumPy is handily applied, calculation time is essentially spent on vectorized exhibit tasks rather than in Python for circles (which are frequently a bottleneck). Further speed upgrades are accomplished utilizing enhancing compilers, for example, python, which permits better command over store impacts. Notwithstanding low-level exhibit tasks, NumPy gives subpackages to direct variable-based math, FFTs, irregular number age, and polynomial control. Bigger logical bundles, like SciPy, are, thusly, based on this foundation. NumPy and comparative tasks cultivate a climate where clients can, without much of a stretch, depict mathematical issues utilizing undeniable level code, consequently making way for logical code that is both straightforward and simple to keep up with.

## Pandas

Another library is called pandas which thusly offers the DataFrame information structure. The panda's library developed from the utilization of clusters in Python's NumPy bundle utilized in numerical and logical registering applications. The panda's library opens another universe of opportunities for information examination. The primary construction from the panda's library is the Series and DataFrame, offering a design to arrange unique kinds of information (strings, numbers, and floats) into a solitary information structure and can undoubtedly apply techniques or capacities to all orbits of the information.

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## Face detection

Identifying a face's location in a photo is the first step in a successful face-recognition process. Recently, a lot of effort has been put into the finding of faces. For example, information-based approaches such as invariant facial methodology, layout matching strategies, and appearance-based techniques have been developed to detect faces in a single photo. In Reference, you may find an outstanding study on facial recognition. Several approaches employ shading data, i.e., detect the districts (skin-map) whose tone is similar to the skin's tone, which can limit the viewing through Region significantly. Aesthetic symbolism is used in the majority of face recognition methods. It is possible that the Viola-Jones algorithm20 presented by Viola in 2001 is the best visual picture computation. In a few articles, methods for finding faces using near-infrared and long-wave infrared symbols were described that use these wavelengths. Warm imagery, in contrast to apparent symbolism, is unconcerned with variations in facial look under altered lighting conditions. Despite this, glasses appear to block off infrared light. Close-IR phenomena and multi-band highlight extraction were proposed in Reference by the developers. Unlike warm discharges, the reach lies inside the reflected portion of the infrared spectrum. It's not exactly the same as a warm picture when it comes to NIR images. The face check plot is predicated on the identification of the eyes and brows inside the skin region after skin division. It was suggested in Reference that a thresholding and projection approach may be used to discern between warm and cool images of a face. The procedure described in Reference is used to arrive at the strategy outlined in this article. Facial recognition is the process of determining a person's features based on a representational image. The following diagram depicts the face-finding calculation process. Use an area developing calculation to smooth the image and divide the individual in the picture to acquire the individual's shape; do morphological duties (close and open) to remove the commotion division. Use a large morphological area (55) and, if necessary, repeat the interaction again. Smooth the projection profiles after calculating two projections equally and upwards. Perform a slew of smoothing activities before moving on to the more complex calculations. Refer to in both an upward and a flat projection; Decide on the district's face by looking at the regions with the most potential for rapid change, such as the core and its largest subsidiaries. Following the computation of the main subordinate, smooth the upward projection, but before looking for the base and most extreme. It was necessary to import all of the dataset's photographs.

Graphical user interface, text, application

Description automatically generated

They are consolidating the neighborhood least to the looking of outrageous qualities in the even projection. See the little green circles for the outrageous qualities in Draw a red rectangular on the first or binarized picture, and afterward concentrate and save the distinguished face picture; Some imperatives are considered to make the locale more precise and vigorous, e.g., the length of the head ought to associate with half of the length of the shoulder. Additionally, higher request smoothing calculation is utilized to smooth the projection bend. District developing calculation is utilized for the division in this face discovery calculation. Area developing calculations have been demonstrated to be a powerful methodology for picture division. The essential methodology of a district developing calculation is to begin from a seed locale that is viewed as inside the item to be divided. The adjoining pixels are assessed to decide whether they ought to likewise be considered as a feature of the item/locale. Assuming this is the case, they are added to the district, and the interaction proceeds until all new pixels are added to the locale. Locale developing calculations differ with the measures used to remember a pixel for the area or not, with the kind availability used to decide neighbors, and with the procedure used to visit adjoining pixels. At the point when the shape or power qualities of the eyes can't be dependably estimated because of impediments (like wearing glasses or shades), the setting attributes are extremely valuable for eye confinement. This is on the grounds that eyes in the face setting generally have a stable relationship with other facial highlights as far as both appearance and construction appropriation **.** the dataset contained two types of folders one is, which have a human face having with glasses, and the second one is without glasses.

Graphical user interface, text, application

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Along these lines, an indicator of facial milestones learned by organized result SVM has been applied to identify the places of the primary concerns of the face and subsequently of the eyes. The contribution of the classifier is a still picture of fixed size containing a solitary face. The result of the classifier is assessed areas of a bunch of facial milestones. Every facial element is processed on a rectangular window. The precision of the classifier has been tried on the LFW information base. The identifier gauges around 97 % of the pictures with the mean standardized deviation between the assessed and the ground truth positions.

## Pattern Recognition

The administrator of the Local Binary Pattern is a grouping element. When it comes to maintaining order on the surface, it's been considered an important factor. A summary of neighborhood dim level design was provided in 1996. In order to describe nearby pictures, the administrator creates a neighborhood surrounding each pixel, restricts its pixels to the focused pixel's value, and then uses the resulting paired esteemed picture fix as a nearby picture descriptor. Eight cycle codes were originally determined by the eight pixels surrounding the focus point when it was first defined for 33 regions.

## Resolution.

In numerous useful video reconnaissance applications, the appearances procured by open-air cameras are of low goal, so tests are completed to set up the base goal of the pictures. Above all else, considering the arrangement of chosen pictures from the LFW information base, the normal size of the facial districts is determined to build up an estimated size of the facial area in the calculation. To diminish how much information to process and to stay away from false-positive acknowledgment, the eyeglasses district is chosen as considered just the eyes zone. An even district around the focal point of the eyes is chosen, thinking that the nosepiece of the glasses is normally positioned at a similar level as the focal point of the eyes in both tallness and width. The still up in the air, considering the distance between the eyes and the sides of the glasses. In these investigations, the width of the standardized eyeglasses locale is 122 % greater than the tallness of the standardized. Since the normal separation from passed on the external eye to the right external eye is 63.86 pixels, the greatest tried width for the standardized eyeglasses locale is 100 pixels and tallness of 45 pixels. Along these lines, the size of the most extreme standardized eyeglasses area is 4500 pixels. The base tried width is 16 pixels and tallness of seven pixels. Along these lines, the size of the base standardized eyeglasses district is 112 pixels. Distinct tests are performed, differing from the most extreme to the base size of the standardized eyeglasses district. It tends to be valued that the connection between the size of standardized eyeglasses locale and the acknowledgment rate follows a logarithmic circulation.

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## Keras

Keras is a smaller and simple-to-learn significant level Python library for profound discovering that can run on top of TensorFlow (or Theano or CNTK). It permits designers to zero in on the fundamental ideas of profound learning, like making layers for neural organizations, while dealing with the low-down subtleties of tensors, their shapes, and their numerical subtleties. TensorFlow (or Theano or CNTK) must be the back end for Keras. You can utilize Keras for profound learning applications without connecting with the moderate mind-boggling TensorFlow (or Theano or CNTK). There are two significant sorts of structures: the successive API and the utilitarian API. The consecutive API depends on the possibility of an arrangement of layers; this is the most well-known use of Keras and the simplest piece of Keras. The successive Model can be considered as a straight heap of layers. So, you make a successive model where you can, without much of a stretch, add layers, and each layer can have convolution, max pooling, actuation, dropout, and bunch standardization. How about we go through significant stages to foster profound learning models in Keras.

Graphical user interface, text

Description automatically generated with medium confidence

Having characterized the Model as far as layers, it needs to pronounce the misfortune work, the enhancer, and the assessment measurements. At the point when the Model is proposed, the underlying weight and predisposition esteem are thought to be 0 or 1, an arbitrary regularly disseminated number, or some other advantageous numbers. Be that as it may, the underlying qualities are not the best qualities for the Model. This implies the underlying upsides of weight and predisposition can't clarify the objective/mark as far as indicators (Xs). Thus, it needs to get the ideal incentive for the Model. The excursion from starting qualities to ideal qualities needs inspiration, which has limited the expense of work/misfortune work. The excursion needs away (change in every emphasis), which is proposed by the enhancer. The excursion additionally needs an assessment estimation or assessment measurements.

## Model 1 (sequentional model):

To apply the model, first of all, several processes were applied such as data augmentation, Region of interest finding, and after that resize the image into 128X128 dimension, I varied the ratio of the pixel, but it provided results at this dimension. The model on the one proposed for help learning and we change it to ImageNet scale picture course of action. The model sequentially requests the data, successfully going to relevant pieces of spatial information at each time step to refine its check of the right name. The two key parts are the sequential thought of the model and the progressive, attentional bottleneck, the two of which we tentatively show add to its solidarity to badly arranged attacks.

We immediately include the huge pieces of the model. For full nuances, we suggest the peruser and the gainful material. The model beginnings by passing the information picture through a "fantasy" net - a convolutional neural net using a modified ResNet50. We use comparable data picture everlastingly steps, so the aftereffect of the ResNet ought to be resolved only a solitary time. The ensuing outcome tensor is then separated along the channel angle to convey a key tensor and a characteristics tensor. To both of these tensors, we interface a fair spatial reason tensor that encodes spatial regions using a Fourier depiction.

This spatial reason is huge in light of the fact that our attentional bottleneck totals over space, causing the spatial plan of these tensors to evaporate, and this reason allows passing on spatial region information. In this study, I applied CNN-based methods to answer a problem. We enroll the various leveled controller for a long while steps, going to the commitment at every movement and dealing with the reaction through the controller to make the outcome. The Top-Down controller is a middle whose previous state is decoded through a "request association," an MLP, into somewhere around one inquiry vector. Each question vector has a comparable number of channels as the keys tensor, notwithstanding the number of redirects in the spatial reason. We take the internal thing between the inquiry vector and key and spatial reason tensor at each spatial Region, achieving a lone channel guide of thought logits. We go through these through a spatial softmax to make the thought map for this inquiry. The resulting thought map is then point-wise copied with the characteristics tensor and the spatial reason. Note that a lone aide is used for all channels. We note the meaning of this under. The expanded worth tensor is added across the spatial angles to convey a reaction vector, one for each question. These reactions are dealt with as the commitment for the current time step connecting them expecting more than one is used. Finally, the outcome from the last outcome is decoded into class logits through an MLP. The cross-entropy incident w.r.t to the ground truth is still up in the air with this outcome.

### Evaluation

Text

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A straightforward measure for remembering pixels for a developing area is to assess force esteem inside a particular span, which is typically given by the client dependent on examination of the picture power. Upsides of lower and upper edge ought to be given. The locale developing calculation incorporates those pixels whose forces are inside the stretch. Marginally unique in relation to this, another technique called neighborhood associated area developing has possibly acknowledged a pixel assuming every one of its neighbors has forces that fit in the stretch. The size of the neighborhood to be considered around every pixel is characterized by a predefined span. In this paper, another model named mean-esteem associated area developing is utilized. It depends on basic insights of the current district. To start with, the calculation processes the mean of power esteems for every one of the pixels right now remembered for the area. A client-given limit is utilized to characterize a reach around the mean. Neighbor pixels whose force esteems fall inside the reach are acknowledged and remembered for the locale.

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Having characterized and accumulated the Model, it needs to make predictions by executing the Model on certain information. Here you want to indicate the ages; these are the number of cycles for the preparation interaction to go through the informational index and the bunch size, which is the number of occasions that are assessed before a weight update. For this issue, the program has run for a few ages 30, and in every age, it needs to finish cycles where the clump size is, and the informational preparation collection has occasions/pictures. Once more, there is no hard guideline to choose the group size. Yet, it ought not to be tiny, and it ought to be significantly less than the size of the informational preparation index to devour less memory.

It was summoned after completing convolution that the picture stack is recoiled. It is defined by the greatest poling along the step's width. It then begins to pan across the image step-by-step. The dimensionality of each element map is reduced by the maximum pooling. Modified direct units are commonly used to provide standardization in convolutional neural networks (ReLU). ReLU removes all of the negative values from the isolated image. The non-linearity of the Model is included in this ReLU cycle. Next, the convolutional neural organization, which is also known as a classifier, was seen in the next layer. In this work, Google is used to classify images and predict user expectations. A cloud-based service named Google Colaboratory is known as Colab. AI and deep learning tasks in Colab require the Jupyter Notebook. The Google Colab provides runtime GPU access that is free of charge. For PC vision and other GPU-powered apps, the Google collaboratory is useful.

Having prepared the neural organizations on the informational preparation indexes, it needs to assess the presence of the organization. Note that this just gives a thought of how well it has demonstrated the informational index, yet it won't realize how well the calculation may perform on new information. This is for straightforwardness, yet preferably, it could isolate information into train and test informational indexes for the preparation and assessment of the Model. It can assess your Model on your preparation informational index utilizing the assessment() work on your Model and pass it similar info and result used to prepare the Model. This has created a forecast for each information and result pair and gathered scores, including the normal misfortune and any measurements have arranged, like exactness.

Keras gives significant level neural organizations by utilizing an amazing and clear profound learning library on top of TensorFlow/Theano. Keras is an extraordinary expansion to TensorFlow as its layers and models are viable with pure TensorFlow tensors. Besides, it tends to be utilized close by other TensorFlow libraries.

## Model 2 (Restnet 50)

RestNet stands for Residual Network, It has many variants that run on same concept but have different layers. Restnet 50 is worked with 50 nural network layers. These layers help to solve complex problems more efficiently as the different layers could be trained for varying tasks to get highly accurate results. We used Keras to build Restnet 50 model. Keras is popular due to the simplicity of building model using deep learning.

To use Restnet 50 in Keras

Step 1. Need to run the code to identify blocks to transform the CNN into a residual network and build a convolution block.

Step 2. Building the 50 layer Restnet model by combining both blocks.

Step 3. Finally train the model for the required task like in our case we are prediciting weather there should be eyeglasses on face or not.

This is the layer formation for restnet50 model to train the model for prediciting the results.

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## Face Masking

The facial covering is a twofold veil to dispense with the interruption from hairs or foundation. The facial covering is physically intended to fit the size of a normal face. A facial covering documented as "Maskface" and a glasses veil are illustrated separately. The facial covering is somewhat fixed, while the glasses veil fluctuates with the subject. The facial covering might be resized to match the picture size on an alternate information base. The "concealed appearances" are shipped off the Gabor wavelet changes, while the glasses veil has to be utilized to cover the face designs.

## Eyeglasses detection

Infrared light can't go through glasses, and along these lines, glasses have shown up as dim regions in a warm picture. One potential arrangement is to distinguish eyeglasses and to prohibit the eyeglasses regions before face coordinating. Accordingly, eyeglasses identification is important to perform warm face acknowledgment. The goal for glasses identification is when taking pictures without glasses then the calculation has told "No Glasses" and afterward stop; while taking pictures with glasses on then, the calculation creates a showing the fragments of glasses two bits of glasses as a paired picture and afterward save the parallel cover picture into a picture document. In particular, the glasses discovery (Maskglasses) calculation is summed up as follows. From face discovery, we have, as of now, sectioned the individual and identified the face in a rectangular locale.

Doing an "AND" procedure on these two locales has delivered the scanning district for glasses recognition. In the glasses looking through locale, the force upsides are more modest than different spaces of the face. To build power, the ROI was isolated to little squares, 7×7 pixels. The mean and fluctuation esteem for every little square was determined. In the event that the glasses exist, there ought to be two little regions with a little mean worth just as little change since the glasses districts are generally homogeneous. One glass region may cover a few little squares. Blend those associated little squares into one and ascertain the mass place as a seed point. Run the district developing calculation to portion the glasses regions. Prohibit the bogus up-sides utilizing the priori information. The hair shows up as dull Region and is effortlessly gotten by the location system characterized previously. The circular segment state of the hair region is altogether different from that of the glasses.

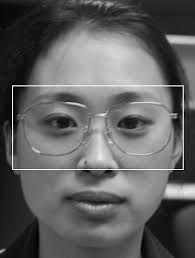


Figure 1.9 Eyeglass prediction

After determining the location of the eyes, the next step is to determine the location of the glasses. We use the left and right eye locations as the left and right lines of the goal area to alleviate eye strain. As a result, the top and bottom borders of the discovery are not fixed in stone based on the orientation of the eyes at the nosepiece location. In this way, it removes the disturbing impact on the eyes and reduces the area of the glasses that are being applied. As a result, the glasses can be detected easily inside this area rather than the entire face area since assuming the foundation is fundamental, the aim is easily identifiable. The process of discovering new glasses is broken down into the preparation and testing phases. The nosepiece of the glasses is selected as the target in the preparation step, and then the selected positive examples are physically modified to reflect this. To begin with, the foundation location is discovered, and then the bad instances are identified organically by editing erratically in the area. It is then created using haar-like highlights and AdaBoost computation to identify the glasses in the target up-and-comer district, and it is used for this purpose.

# Chapter 5

## Results and Analysis

Security systems, intelligent advertising, and marketing might all benefit from glasses-detection technology. Glasses detection on facial photos has been studied in this research. The original LBP and RLBP are compared by altering the parameter in a normalized eyeglasses region. All of these variables are examined, including resolution, alignment of normalized pictures, as well as LBP operator divisions.

A collage of people

Description automatically generated with medium confidence

Warm face acknowledgment turns into a functioning examination course in human ID since it doesn't depend on light conditions. Face discovery and eyeglasses location are fundamental stages preceding face acknowledgment utilizing warm pictures. Infrared light can't go through glasses, and consequently, glasses have shown up as dull regions in a warm picture. One potential arrangement is to recognize eyeglasses and to bar the eyeglasses regions before face coordinating.

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In warm face identification, a projection profile examination calculation is proposed, where district developing and morphology tasks are utilized to fragment the body of a subject; then, at that point, the subsidiaries of two projections flat and vertical are determined and dissected to find a negligible square shape of containing the face region. Obviously, looking through the district of a couple of eyeglasses is inside the recognized face region. The eyeglasses recognition calculation should create either a paired veil assuming eyeglasses present or an unfilled set if no eyeglasses by any means. In the proposed eyeglasses identification calculation, block handling, locale developing, and a priori information—the exploratory consequences of the proposed face location and eyeglasses identification calculations. For eyeglasses identification, there are a few face pictures that have eyeglasses on. "Genuine positive" signifies the distinguished eyeglasses are in reality evident, "Bogus positive" (0) implies the identified eyeglasses are bogus in reality no glasses present in those pictures; "Genuine negative" signifies no eyeglasses are recognized in glasses-missing pictures; "Bogus negative" signifies no eyeglasses are recognized in glasses-present pictures. one bogus positive (the featured hair region) is eliminated due to its low Solidity esteem. The subtleties are uncovered in the inscription. The general presentation is estimated by the mean of covering proportions, glass, which is an awesome exhibition considering a superb location. Remember that the ground facts of eyeglasses are indicated by two square shapes that make rM(glass) < 1. Now and again, just incomplete spaces of eyeglasses were distinguished in light of the fact that the missed glasses regions were warmed up my face and seemed more brilliant. Likely a similar explanation caused the missed glasses. The undetected eyeglasses may lessen the presentation of warm face acknowledgment as opposed to bombing the acknowledgment interaction.

## Experimental Results

### Sequential Model Results

The Sequential model based on CNN is trained with images and without images to predict the values of results. After adding other parameters like image resizing and preforming feature engineering and splitting dataset into test and train and analyse the results and found in this model loss value is high although it accuracy is also equivalent to restnet50 model. High the loss value lesser the accuracy.

Table

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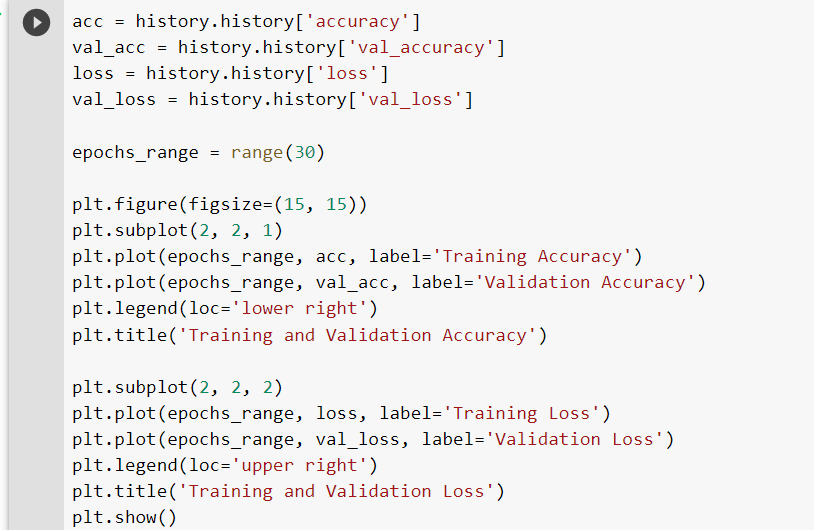
### Restnet 50 Results: The Restnet50 based on CNN model is trained and validated using images withglass and without glasses which dvidides the data into training and testing. The total experiments is carried out in three parts: RGB pictures. The experiment of all epochs done show the performahce measures accurancy, precision and loss.

A screenshot of a computer

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## Evaluation

We have shown that the consecutive consideration model further develops power against an assortment of assaults and assault qualities. Besides, we have seen that we can expand precision and protect better against more grounded assaults by unrolling the model for additional time steps. We presently go to examine a portion of the properties of the subsequent assault pictures and methodologies.



Chart, line chart

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To make the spatial part, and therefore the effect of the thought bottleneck more expressed, we change the ResNet plan to make the last outcome have greater spatial angles. This is done by changing the means to 1 in everything with the exception of the resulting waiting square. For ImageNet input (128 × 28 pixels), the resulting guide is 28 × 28 pixels colossal. The proposed model provided accurate results; the graphical representation of the training loss and valuation is given above. As shown in the diagram, the training loss decreases gradually while the validation loss varies with the level of training of the model.

## Comparision with other pre trained models:

There are certain other deep learning models that have been pre trained to detect eyeglasses on face or not. We used CNN model for image classification process.

The CNN model based sequential model attains 46% accuracy in the study of glass detection after training the model with some images of with glasses or without glasses, whereas Restnet 50 gives 57%. If we compare both results loss values is high in sequential model, but restnet 50 loss values is less than this so this is good to get results.

# Chapter 5

## Conclusion and future work

In this work, I am working to classify the human face as having eyeglasses among the others with no eyeglasses on their faces. The research has been based on machine learning techniques. The system has detected the human face for several purposes. It is a significant task to find the eyeglasses from the human beginning where machine learning plays an essential role in solving the various problems of life. In this research, I have also utilized this one to conduct this research and provide more accurate results than the other state-of-the-art schemes. After human face detection, the primary task of detecting the target region is detecting the eyeglasses and classifying them.

To obtain the results, two classification model are used to identify if there are eyeglasses on human face or not. The dataset utilized in the study of image processing, and trained the model to detect the eyeglasses on face, along with various other attributes are also used like feture selection, image resize to reduce the complexity of model etc. The Restnet50 based on CNN modal technique is used to extract the results with accuracy

As per the literature, a significant amount of work has previously been done in anticipating weather the face has glasses on there face or not using their pictures. However, accuracy enhancement, as well as real-time testing and deployment, are the few factors that must be prioritized. However, in the future, I will improve the accuracy of the model and will try to execute it for real-time applications, and will also focus on improving the results of the existing model.

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